IADIS International Journal on Computer Science and Information Systems
Vol. 8, No. 2, pp. 51-71
ISSN: 1646-3692

TOWARDS THE USE OF FACTOR ANALYSIS FOR USER-CENTRIC EVALUATIVE RESEARCH IN INFORMATION SYSTEM

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ABSTRACT

The potentials of factor analysis are summarily to reveal underlying factor structures, test the theory of analytic user-centric models, and demonstrate their causal relationships. Its common applicative types are: Exploratory, confirmatory and structural equation modelling techniques. This paper, underscores it basically due to its multidimensional and multivariate data analytic knack. Analytically, it manages the multidimensionality of user-centric data and yet presents replicable result. Therefore, our enthusiasm hopefully is to whet the appetite of IS researchers, particularly those that are engaged in user-centric evaluative research in a way that motivates them to pursue additional knowledge about the technique. However, this technique has matured in other related fields, such as: The Cognitive and Behavioural sciences, Human Computer Interaction and Psychology from where IS draws from in terms of user-related studies. This is not yet the case in IS. An algorithmic like framework is therefore introduced, and its use to assess an IS with the purpose of underscoring the use of the FA methodology is reported in fulfillment of the aim of this paper. As a result, a measurement model is presented. The use of the FA technique is therefore recommended based on the degree of validity and reliability demonstrated by the model, which is significantly replicable.

KEYWORDS

Factor analysis, user-centric evaluation, multivariate statistical analysis, measurement model, cognitive and behavioural sciences, and human computer interaction

1. INTRODUCTION

User-centric evaluative studies (research) in Information System (IS) usually attract large volume of data, and managing them to provide results that are replicable is often tedious. But, the core of user-centric evaluative research in IS is User-centricity. It projects the need to produce software (systems) to help users solve problems as they conceive it, and not as the designers of the system do. It is also about understanding the user and collaborating effectively with them through evaluative studies. As a result, informed choices are made based on deep understanding of users about what software to build for users' use without personal bias and assumption (Patton, 2007). To make these informed choices multivariate data analytic techniques are often required handling user-centric data.

These data are what managers of Information Systems (ISs) in organizations often rely on for favourable user-centric evaluative outcomes in order to guide useful decision-making. But, evaluating ISs is still very difficult, since there is yet no unique model to evaluate all kinds of ISs (Islam, 2009). The implication of this is that a continuous and focused evaluation of IS is required for the provision of better evaluative models that will improve existing IS evaluative methodology. ISs is pervasive; this originates from the understanding that current IS "do not bound their operation only in an organizational setting, but they also include other possible settings, such as domestic or public settings. Consequently, IS provides useful services that fit user's requirements and needs" (Kourouthanassis and Giaglis, 2007; Karaiskos, 2009). Thus, adopting any kind of IS would require the careful assessment of factors that centers on user-system interactivity as well as usability with respect to ease of use. This ought to be the emphasis of modern IS evaluation, and should be based on (i) how ISs serve organizational change and (ii) the user in the organization (Klecun and Cornford, 2005; Lagsten, 2011). It is essential that this type of evaluation be focus on the user, since it is the user who will determine the usefulness of IS. This cannot be derived from investigating how ISs serve organizational change. To this end, expected result should be reliable; it should not only be generalizable, but replicable towards the change and betterment of an organization and its IS. In this paper, the focus is therefore on the user. It is not on (how and) the extent ISs serve organizational change, which can also be examined from users' perspective.

This paper therefore builds on some initial studies, such as Akhigbe, Afolabi, Udo and Adagunodo (2011a), Akhigbe, Afolabi, and Adagunodo (2011b), Akhigbe, Afolabi, and Adagunodo (2012), and Akhigbe (2012). These experiences occasioned the understanding that specialized training of some sort may be needed to use the FA technique. This should not be considering the scores of studies within IS that report its use. It is particularly also worrisome to note that the reports (projection) are often miserly done. This is not acceptable for a robust field like IS. Worst still, is the finding that FA as a Data Reduction (DR) and modeling technique to this very moment is not even contextualized. It was very disturbing and frustrating to know that it is the miserly reporting of the use of the technique that is responsible for why naïve users cannot take advantage of it. Essentially, researchers (not only naïve users) using the technique should be comfortable with FA's use and also able to find their way around it for user-centric evaluative research in IS.

This paper therefore seeks to introduce a step by step algorithmic like approach. So as to contribute to the need to highlight the use of the FA technique considering its usefulness for data reduction in user-centric evaluative research in IS. Furthermore, this paper draws from the work of Williams, Onsman, and Brown (2010) where a five-step guide is provided to assists novice researchers with a simplified approach to undertaking Exploratory Factor Analysis (EFA). The work provided an FA protocol with the intention of educating kindred paramedic educators and researchers in the use of EFA. What is done differently in this paper is that a wider focus is pursued, in that all the three types of FA is covered. Here, we aim to contribute to (i) the need to underscore the FA, and (ii) debate the need to contextualize the FA as a modeling and DR technique to the best of our knowledge. The belief is that even naïve users should be able to easily understand and leverage on the FA technique for user-centric modeling and data reduction in IS. The Web Search Engine (WeSE) - a type of Information Retrieval (IR) system as example of Information system is used to fulfill this aim. Additionally, following (Chen, Chang, Hung, and Lin, 2009), the EFA, the Confirmatory Factor Analysis (CFA), and the Structural Equation Modeling (SEM) techniques were used for FA in this paper. The paper progresses with related literature in Section 2, while in Section 3, FA is underscored; and in Section 4 the algorithmic like framework is presented. As well, in Section 5 IR system as example of IS is presented. The study's methodology, data analysis and conclusion are presented in sections 6, 7 and 8 respectively.

2. RELATED LITERATURE

Existing works that use the FA abound in the context of IS, but a few relevant ones are presented (e.g. Muylle, Moenaert, and Despontin, 2004; Yang, Cai, Zhou, and Zhou, 2005; Kiraz, and Ozdemir, 2006; Lee, Theng, Goh, and Foo, 2006; Wu, Shen, Lin, Greenes, and Bates, 2008; Islam, 2009; Chen *et al.,* 2009; Sumak, Hericko, Pusnik, and Polancic, 2011; Akhigbe *et al.*, 2012 and Akhigbe *et al.,* 2011). Muylle *et al.* (2004) developed a model with desirable psychometric properties for measuring the user satisfaction of websites. The IS success theory was used to underpin the model and its constructs, while the study's empirical data analysis was carried out using the FA technique. Similarly, in Yang *et al.* (2005), a user perceived service quality of information model was presented in order to assess the factors that influence the design of an information presentation portal. The EFA, CFA and SEM were used to carry out the FA that resulted in a five-dimension service quality instrument. However, Muylle *et al.* (2004) and Yang *et al.* (2005) did not adequately describe the FA technique nor highlight its importance for user-centric evaluative research in IS and the nitty-gritty of its use. In Kiraz and Ozdemir (2006) the FA technique was employed for data analysis to show that different educational ideologies may have different effects on teachers' technology acceptance. But, like Muylle *et al.* (2004) and Yang *et al.* (2005) the use of the FA was only mentioned. These works were silent on whether it was the three techniques of the FA, namely: the EFA, CFA and SEM, or only one of the techniques that was used for its data analysis. It is not good enough to come across miserly reporting only and in all the FA related paper one finds, especially when one needs guidance on the subject. It is also annoying when a naïve reader is left to find guidance with respect to how to use the FA from the FA result presented. There is definitely no circumstance under which the withdrawal of necessary details (miserly reporting) will be sufficient enough to help users in IS. This will continue to be unacceptable, and thus requires good attention for this incongruity to be mitigated.

Using the FA, user-related data was analyzed to identify groups of features that supported students' document evaluations. The data was collected during IR interaction stages to provide design implications for an IR interface that supports students' evaluations of documents in Lee *et al.* (2006). The researchers used digital libraries as examples of IR systems, and enhanced objective relevance and tackled its limitations by conducting a quantitative study to understand students' perceptions of features for supporting evaluations of subjective relevance of documents. Though the work was insightful, like other related works (e.g. Muylle *et al.,* 2004; Yang *et al.,* 2005; and Kiraz, and Ozdemir, 2006), naïve users will not be able to learn the use of the FA based on the miserly way the use of the FA technique was reported. In other related works like Wu *et al.* (2008) and Islam (2009), this incongruity remains the same. For instance, in Wu *et al.* (2008) the FA was used to examine an extended technology acceptance model. The investigation was meant to determine the effect of trust and management support issues on the acceptance of an adverse event reporting systems by healthcare Professionals. The final result was inciting, but the reporting followed the same pattern with that of earlier reviewed works. Both the CFA and the SEM was applied and very evidently were used to resolve reliability and validity cum causal issues. But, replicating the approach the researchers used is very difficult to fathom and follow. Comparably, the research effort in Islam (2009) developed a model to measure user satisfaction and success of an IS using a web base virtual meeting tool as example of IS. It was very easy to know that the EFA of the FA was used in the research, and some level of details were also provided, which users may be able to replicate (follow) in a similar study. But other aspects, particularly when examining the reliability and validity of the model, the concept of Item-to-Total correlation was vaguely presented. Good enough, users could understand that it is meant to test the model's reliability and validity perhaps, but the question of how to put it to use remain fuzzy.

Likewise, the FA was also used to develop an instrument to assess the quality of a web-based learning system for nurses' continuing education (Chen *et al.,* 2009). The researchers (Chen and Colleagues) used the CFA to verify the instrument's construct validity based on quality dimensions. It was very easy to know that the CFA was the FA type that was used for the study. And the reason was provided, which was that since prior theories or hypotheses are available, the CFA was preferred to EFA. This was a major strength of the work considering the ongoing debate. But, the researchers introduced the Squared Multiple Correlation (SMC) to test the reliability of the model. However, the rationale for introducing SMC was not provided; one would have expected the use of the other FA that can be used to test reliability for the sake of clarity and replicability. Also, the use of the SEM to demonstrate the proposed model's fit needs an expert to fathom. So, as was the case with other earlier reviewed works, the one in Chen *et al.* (2009) was also not reported in details, thus grossly also not underscoring the FA. In Wu *et al.* (2008), Islam (2009) and Chen *et al.* (2009), though the works are stimulating, they lack the use of sufficient details to underscore the use of the FA technique. While that of Chen *et al.* (2009) was fair in terms of the provision of guidance in the use of FA, that of Wu *et al.* (2008) and Islam (2009) especially with respect to their report on SEM did not help matters. Thus, naïve users and curious readers would not benefit much since they will not be able to take advantage of it.

In Akhigbe *et al.* (2012) the use of the FA for the characterization of Decision Variables (DVs) or items using WebSEs as case study in a user-centric experiment was demonstrated. The implication of their research was that important system resources could be conserved by applying the FA technique. Other user-centric studies that used the FA technique for data analysis that are worthy of just mentioning due to time and space are: Akhigbe *et al.* (2011), Sumak *et al.* (2011), Saracevic (1995) and Akhigbe (2012). However, the effort of Chen *et al.* (2009) and Sumak *et al.* (2011) are among the few that were not too miserly in their report of the FA technique. We thus argue that IS research deserves a better systematic documentation and a generous reporting of the FA technique. This would adequately underscore its usefulness and provide sufficient guidance for naïve and intended users in IS domain.

Considering the fact that IS is perverse, there ought to be reference documents on how to use the FA, within its context to assist naïve users to find their way easily with its use (Henson and Roberts, 2006; Sun, Chou, Stacy, Ma, Unger, and Gallaher, 2007; and Smith and Albaum, 2010). The works of Henson and Roberts (2006), Sun *et al.* (2007) and Smith and Albaum (2010) provided the underpinnings that our argument draws and builds on to actualize its aim. Henson and Roberts (2006) provided a detailed explanation of the use of the technique, thus recommending it for inferential data analysis. The target beneficiaries were researchers in Education, Psychology and the Cognitive sciences. Similarly, in Sun *et al.* (2007) it was contextualized for the Social sciences, unlike in the IS domain. In the field of marketing research it is used for data analysis in order to examine consumer lifestyle and personality type. However, the FA does not have a foundation up till now in IS like in other fields talk less of seeking further grounding in order to appropriately use it as requested in Henson and Roberts (2006), Petter, Delone, Mclean, (2008), Sun *et al.* (2007) and Smith and Albaum (2010).

3. UNDERSCORING FACTOR ANALYSIS

The FA, particularly the SEM has evidently become one of the techniques of choice for researchers across disciplines (Hooper, Coughlan, and Mullen, 2008) particularly for multivariate data analysis that is typical of user-centric evaluative research. The norm is that if prior theories or hypotheses are available, CFA is usually preferred to EFA (Nunnally and Berstein, 1994 as cited by Chen *et al.*, 2009). To properly accentuate the FA and thus underscore its use and canvass the need to contextualize it, it will take more than just a paper of this nature. Therefore, the overarching attempt in this paper is to whet the appetite of IS researchers (and others who need the approach) in a way that will hopefully motivate them to pursue additional knowledge about the FA. Thus, the FA and its associated techniques are briefly highlighted in the next subsections 3.1 to 3.3 of this paper.

3.1 Brief Overview of the FA

It was necessary to examine a real life (or an example) IS using the technique, and thus very easily stress the importance of the FA for user-centric evaluative research in IS. This paper therefore adopts the WebSE and evaluated it as an IR system using the FA. That Search Engines (SEs) are the commonest application of IR systems, and the fact that several users of the Web use one SE or the other also added to the motivation for its adoption. This is reviewed further in section 4.

Historically, the theoretical framework for FA is credited to Pearson and Spearman. In Kieffer (1999) as cited by Henson and Roberts (2006), it was noted that Spearman through his work on personality theory, provided the conceptual and theoretical rationale for the technique. The technique involves the use of both the EFA and CFA, and at times the SEM. As a multivariate statistical procedure, the FA has many uses, among which are to: (i) reduce a large number of variables into a smaller set of variables (also referred to as factors), (ii) establish underlying dimensions between measured variables and latent constructs, thereby allowing the formation and refinement of theory, and (iii) provide construct validity evidence of self-reporting scales. As stated by Nunnally (1978) and cited by Thompson (2004), and Williams *et al.* (2010), *"... factor analysis is intimately involved with questions of validity ... Factor analysis is at the heart of the measurement of psychological constructs".* Constructs of this sort are what is examined in user-centric evaluative research. Additionally, in human-user related studies researchers would commonly want to explain the most variable occurrences with the least one. And in order to achieve parsimony, researchers also regularly strive to explain the most shared variance of measured variables - items. A most succinct and logical way to do this explanation is to use the fewest possible unobserved (latent or synthetic) variables. Theoretically, the FA technique is suitable for this and even usable to explain a larger set of, say *x* measured variables with a smaller set of, say *y* latent constructs. Usually, a matrix of association can be used to model the relationships that exist between the *x* measured variables. And the result of this model is a smaller set of *y* latent constructs. One advantage of this approach is that the *y* latent constructs can be used as variables in subsequent analyses. They can also be seen as actually producing (causing) the observed scores on the measured variables (Thompson and Daniel, 1996 as cited by Henson and Roberts, 2006).

Basically the goal of FA is to describe a set of say z random variables in terms of a smaller number (say k). In rational comparism, k will become less than z (i.e. $k < z$ of unobserved constructs called factors). Furthermore, a factor, like a regression model is a linear combination of a group of variables (items) combined to represent a scale measure of a concept. But, the variables must represent indicators of some common underlying dimension or concept such that they can be grouped together theoretically. This theoretic can be harnessed mathematically to be able to use the FA for its analytics. Thus, with the FAs the number of variables used to explain a relationship or to determine which variables show a relationship can be reduced. In more mathematical terms, these factors can be determined by interpreting coefficients in a factor model, called loadings. Following Grau (1997), this factor model is described using formal specification as follows;

$$y_i = a_{i1} f_1 + a_{i2} f_2 + a_{i3} f_3 + \dots + a_{in} f_n \quad (1)$$

Where;

y_i is the ith variable;

a_{ij} is the jth factor loading ((where $j = 1\ to\ n$) for the ith variable); and

$f_1, f_2, \dots f_n$ are the uncorrelated common factors

In (1), for the variance of y_i to be explained by f_j, the factor loading - a_{ij} must be squared. The variance of ith variable consists of two parts (i) the variance specific or unique to that variable, and (ii) the variance that is common to all variables in the form of the n factors. However, the second part is the communality - the sum of the squared factor loadings across the n factors for the ith variable. There is Partial Pair Wise (PPW) correlations between the variables, which should be small, compared to the Original Correlations (OC) after controlling for all other variables. The implication of this is that the Common Factor Model (CFM) just described can explain the overall variation. It is necessary to note that if the PPW correlations vary slightly from the OC, or larger in absolute value, it means that the CFM is inappropriate for the data. Additionally, to improve the CFM, variables must be removed and (or) added to the set included in the FA (Grau, 1997).

But, in y_i, i can be $i = 1\ to\ p$ set of linear equations, which can only be handled simultaneously. And for multivariate data analysis as is in user-centric evaluative research, more than one factor with several users obligated to respond portend the need for a model to harness them, all in one. This is where the concept of a matrix of association (correlation matrix). With this concept, pushing the modeling that already started with (1) becomes easy. This is because at this point the matrix of association is usable to model (represent) the relationships occasioned by y_i, where there are p relationships. Nevertheless, correlation matrices are often useful for (i) calculating system's efficiency, (ii) analyzing multivariate items (properties), and (iii) handling multidimensional views that develop well into useful goodness-of-fit. The correlation matrices are also useful in the measurement of cognitive issues. Usually, these issue(s) may be an attempt to examine a system's efficiency from users' perspectives. And often, the perspective of the user is commonly investigated using multivariate items (properties), which are multidimensional in views. The challenge this multivariate/multidimensional influence presents can be handled using a matrix of association (Gradoni, Primiani, and Moglie, 2013; Akhigbe *et al.*, 2012; So and Wong, 2010). And using the Frobenius norm of a matrix (So and Wong, 2010), this multivariate/multidimensional associations can be easily modelled - represented as a matrix say Q as follows;

$$Q = \sum_{i=1}^{k} \sum_{j=1}^{k} \left| a_{ij} \right| \tag{2}$$

Where Q is a matrix of order $(i \times j)$, and a_{ij} is the element of the matrix which can be a combination of the responses (ratings) of users, based on the items made available for users to respond to. Following Gradoni *et al.* (2013), (2) can naturally be handled by invoking the concept of a correlation matrix to analyze the many relationships depicted by the elements (a_{ij}). However, these relationships are many and similar, and exist in a multivariate situation. As a result, it is easy to model them using the matrix of order $(i \times j)$. Accordingly, the correlation matrix of Q in (2) can be obtained to capture this modeling of similar and many relationships following Gradoni *et al.* (2013) (see equation 3). This reduces the correlation matrix into a parsimonious meaningful representation of the entire matrix that is replicable and also fit into the original data set. Mathematically this is represented in (4). To do this will ordinarily (manually) take a very long and tedious time depending on the order, like in this case $(i \times j)$. This order is usually determined by the population size (the number of users of the system under investigation), and the number of items presented to the user to court their responses.

$$q = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1j} \\ a_{21} & a_{22} & \dots & a_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ a_{i1} & a_{i2} & \dots & a_{ij} \end{bmatrix}$$

(3)

As is in (3), the correlation matrix in (3) can be Transposed (Tr) to become (4), which is presented as follows;

$$q_{Tr} = \left[Tr(\sum)\right]^{-1/2} \sum \left[Tr(\sum)\right]^{-1/2}$$

(4)

Having fulfilled specific conditions (which are presented in the next subsection), and based on the goal of the particular research; the FA is introduced beginning from the EFA. The EFA is used to uncover the underlying factor structure of the data set (characterized using the matrix in (2 and 3)), while the CFA can be used to test the reliability of the resultant factor structure (model). The CFA can also be used to achieve a level of goodness-of-fit of the model, while the SEM - a type of CFA (though does more in terms of structural modeling) is well suited to show the cause effect of the variables that the model is composed of (Stephenson, Holbert, and Zimmerman, 2006). This cause effect uses the Bayesian algorithm, which scope is beyond this paper. Additionally, no doubt can be entertained in the use of the FA technique with respect to validity. The implication of this is that results that are replicable due to parsimonious solutions have been well taken care of in FA (Nunnally, 1978; Henson and Roberts, 2006). Hence, Kerlinger (1979) adds, FA is *"one of the most powerful methods yet, for reducing variable complexity to greater simplicity".* As a result, issues of validity are to be taking very seriously in the use of FA as it is in the heart of both psychological and cognitive constructs (Nunnally, 1978, Henson and Roberts, 2006). Therefore, validity is one of the major reasons among others why FA is suitable and should be encouraged for use in user-centric (related) studies in IS.

3.2 Types of FA

Researchers have stressed that the process of theory building and construct measurement are joint bootstrap operations in multivariate data analysis. Thus, FA is capable of integrity measurement and guide for further theory refinement (Hendrick and Hendrick, 1986 as cited by Henson and Roberts, 2006). As regards construct validity, utilizing operational referents for constructs of a theory is meant to test if the constructs interrelate as the theory states (Gorsuch, 1983 as cited by Henson and Roberts, 2006). Therefore, FA is primarily used for the development of operational constructs and their representative theoretical constructs.

Essentially, the concept underlying the use of Multivariate Methods (MMs) in user-centric investigations is simplification. That is reducing a large and possibly complex body of data to a few meaningful summary measures. This could also imply the identification of key features and any interesting patterns in the data. To do this, MMs deal with the simultaneous treatment of several variables (Krzanowski and Marriot, 1994a and b; Sharma, 1996). Hence, *"In a* *strict statistical sense MMs concern the collective study of a group of outcome variables, thus taking account of the correlation structure of variables within the group"* (Ruel, Levin, Armar-Klemesu, Maxwell and Morris, 1999). How the FA achieves these feats as a multivariate data analysis technique is briefly presented in the next subsections.

3.2.1 The EFA in Brief

EFA is renowned for data analysis since it could remove redundant features and identify relationships so that groups - factors describing (most of) the original data would be discovered (Lattin, Carroll, and Green, 2003; Netemeyer, Bearden, and Sharma, 2003 as cited by Lee, Theng, Goh, and Foo, 2006). Like Williams and Colleagues accounted, *"EFA is heuristic. In EFA, the investigator has no expectations of the number or nature of the variables. And as the title suggests, is exploratory in nature. That is, it allows the researcher to explore the main dimensions to generate a theory, or model from a relatively large set of latent constructs often represented by a set of items".* Therefore, the basic objectives of the EFA are to (i) reduce the number of variables, (ii) examine the structure or relationship between variables, (iii) detect and assess the unidimensionality of a theoretical construct, (iv) evaluate the construct validity of a scale, test, or instrument, (v) develop parsimonious (simple) analysis and interpretation, (vi) address multicollinearity (two or more variables that are correlated), (vii) develop theoretical constructs, and (viii) prove/disprove proposed theories (Williams *et al.,* 2010).

To conduct the EFA, some precautions (and choices) are very important to take, depending on the goal of the particular data analysis. However, the use of the principle components analysis with varimax rotation procedure is quite common with 0.4 factor loading. This allows the extract of the right factors to form the expected factor structure or measurement model. In carrying out the extraction one of three or all three heuristics could be used: (i) Factors above the "elbow" of the scree plot are extracted, (ii) factors that had eigenvalues greater than 1 are extracted, and (iii) eigenvalues from a dummy dataset are compared with eigenvalues from the real dataset, and factors in the real dataset that had eigenvalues higher than those in the dummy dataset are retained (Lattin *et al.,* 2003; Netemeyer *et al.,* 2003 as cited by Lee *et al.,* 2006). The EFA is commonly used to carry out this type of FA that entails determining the theoretical constructs that underlie a given data set and the extent to which these constructs represent the original variables.

3.2.2 The CFA in Brief

The CFA is often used to carry out the corresponding FA needed to examine the reliability and validity of the measurement model (Wu *et al.,* 2008). Thus, the CFA provide the technique to empirically test the measurement properties of models. With the CFA technique, a set of theoretical relationships between measured variables and their respective latent constructs are tested. Hence, primarily the CFA assists researchers to understand the empirical properties of theoretically guided constructs in their research (Stephenson *et al,* 2006). This is possible since every theoretically guided constructs has empirical properties. This allows the CFA to guide researchers to advance and test the measurement properties of a scale or its subscales a priori. This is important because the conclusion of any research is only as good as the measurement of the concepts used in the research (Bollen, 1989 as cited by Stephenson *et al,* 2006).

According to Williams and Colleague, the CFA assists the researcher to test a proposed theory or model (CFA as a form of structural equation modeling). In contrast to EFA, it has assumptions and expectations based on priori theory regarding the number of factors, and which factor theories or models best fit. Like in EFA, the extraction methods commonly used in factor analysis are (i) Principal Components Analysis (PCA), (ii) Principal Axis Factoring (PAF), (iii) maximum likelihood, (iv) unweighted least squares, (v) generalized least squares, (vi) alpha factoring, and (vii) image factoring. In literature, both the PCA and the PAF still remain the most commonly used, despite the raging debate on which of them to use. It is important to stress that the practical differences between the two are often insignificant, particularly when variables have high reliability or where there are 30 or more variables (Thompson, 2004; Gorsuch, 1983). PCA also remains the default method in several statistical programs (software), and it is recommended when no priori theory or model exists. Thus, it was suggested in establishing preliminary solutions in EFA (Thompson, 2004; Pett, Lackey, and Sullivan, 2003; Gorsuch, 1983).

3.2.3 The SEM in Brief

In the use of the SEM technique, another common way to use the FA is provided. Thus, using the SEM allows the simultaneous estimation of a system of hypothesized relationships among observable and latent variables. The purpose of this estimation is to determine if these associations between the “hypothesized relationships” are consistent with the sample data obtained usually from the result of EFA and CFA statistical processes. The use of SEM involves three primary steps: Specification, estimation, and evaluation. This technique at the end of the three steps is used to show a model’s goodness of fit, its multivariate normality, and the model’s modification as well as its structural model. The principal advantage of SEM is its ability to model constructs as latent variables. Researchers are thus empowered to extract measurement errors, such that only the systematic relationship between latent variables remains. These latent variables are the underlying constructs that are not directly tapped by any one set of measures. In latent variable modeling, a construct’s unreliability is accounted for in the resultant measurement model. The respective error terms of the measurement model especially for measured variables are used to estimate the unreliability (measurement error) that exists between the measured and latent variables. As a result, both random and uniqueness errors are removed in such a way that construct’s reliability remains 1. This means that the parameter between the measured variables and their respective latent variable reflects the systematic (true) relationship of measurement that is corrected in order to avoid unreliability. In the use of SEM to evaluate causal models, the structural part of the model can theoretically be specified as either recursive or non-recursive. For non-recursive models, they contain reciprocal causation, feedback loops, and have correlated disturbances; thus they reflect more complex processes. Basically, a process of influence that simply does not need to move from left to right within a model is referred to as a re-cursive model. Usually, when a user-centric model (especially the measurement model) is proposed based on the result gotten from an EFA process, the model needs to be empirically tested. This is done using the data collected from a survey within the relevant context (Cudeck, du Toit, and Sorbom, 2001; Joreskog, 1973; Duncan, 1975; Hoyle and Kenny, 1999; Bollen, 1989 as cited by Stephenson *et al*, 2006).

4. AN ALGORITHMIC FRAMEWORK TO USE THE FA

A typical FA process may be considered to involve all the three techniques of EFA, CFA and SEM as the case may be. The steps to apply in ensuring this can be summarized with the use of an algorithmic like framework (see Figure 1). The particular unique feature of the algorithmic like framework is the inclusion of the five step protocol by Williams *et al.* (2010) (see Figure 1).

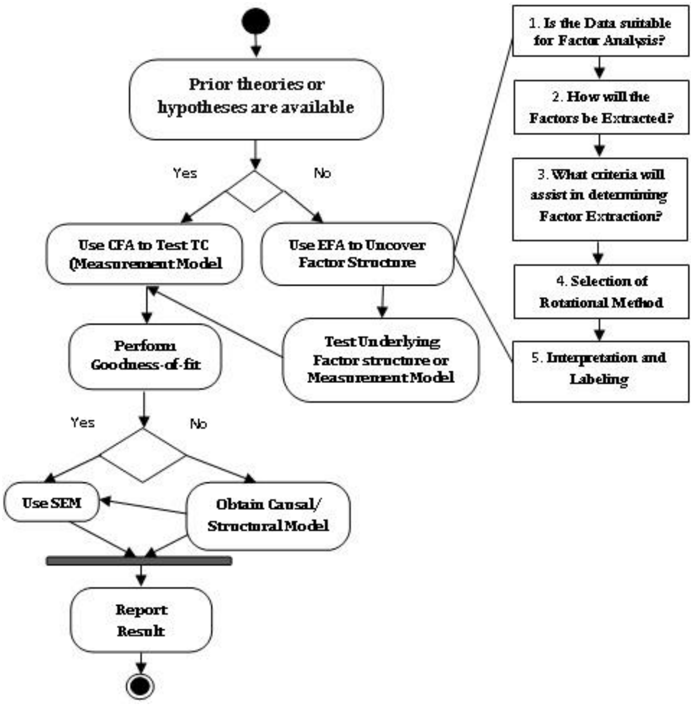

Figure 1. The Algorithmic like Framework (for employing the FA techniques)

The concept of this protocol serves as useful theoretical underpinnings for our approach as its focus on the use of an algorithmic protocol to help the use of the EFA. The framework (see Figure 1) is presented using the activity diagram – a tool for describing business processes, procedures or algorithms. It could also be used to show control flows from one activity to another (Ojo and Estevez, 2005) as demonstrated in Figure 1. In the algorithmic like framework, the first activity "Prior theories or hypotheses are available" has implication. That is the researchers would need to establish if the latent construct to be measured is consistent (has a priori) with the theoretical structure imposed on the data. If not, "No" as depicted in Figure 1, the EFA is employed following the five steps in the top right hand side as proposed by Williams *et al.* (2010). Secondly, the resultant theoretical (hypothesized) structure, often also known as measurement model is empirically tested for reliability and validity using the CFA. Thirdly, the SEM can be employed to provide the goodness of fit of the measurement model, depending on the goal of the particular data analysis. And if necessary, the causal model of the measurement model can be developed using the SEM technique, but this depends on the goal of the data analysis (Anderson and Gerbing, 1988).

Finally, the appropriate result is reported with the FA technique providing sufficient statistical rigor for both multidimensional and multivariate data analysis of this nature. Thus, researchers (i) would be able to fully capture the intricacies of IS processes, and (ii) understand completely the very many processes of interrelated variables in IS evaluative research. However, this technique is not free of weakness, despite the strengths presented so far. There is much more to this discussion than can be provided here. As a result, readers are requested to consult Schumacker and Marcoulides (1998), Stephenson *et al.* (2006), Henson and Roberts (2006), Smith and Albaum (2010), Kaplan (2000), Tukey (1977), Cheung and Chan (2004) and other relevant texts for details on (i) the strengths and limitations of the FA, and (ii) how and when to use them.

5. IR SYSTEM: AN EXAMPLE OF INFORMATION SYSTEM

In the evaluation of the example IS (IR system), there is need for a paradigm change from the prevalent system-centric methodology to the user-centric methodology. This change is paramount so as to easily assess IR system from a holistic perspective. IR systems are systems that assist users to locate documents that should contain information that satisfies their information need in response to their query (Kumar *et al.*, 2005). The WebSE, question and answering systems, and information seeking and support system (Ong, Day, and Hsu, 2009; Mandl, 2008) are examples of IR system. In addition, about 85.6% of those who use the Internet use one WebSEs other (Rubel, King, Wiley, and Murray, 2009; Jansen and Spink, 2006).Thus, making it one of the most used IS, hence its adaptation for use as a case study in this paper. The development of IS and its evaluation especially from user's perspective is complex and usually require interdisciplinary teams as well as techniques. This feat is the same for user-centric evaluation of IR, which has experienced huge growth in the past decade considering the corresponding growth of the Internet because of the ever increasing number of users on a daily basis. So far, the evaluation of IR systems has been mostly driven by the Cranfield-philosophy (system-centric) than the user-centric philosophy. While the system-centric philosophy is used in the evaluation of IR system in laboratory environments, certain amount of abstraction and control is required (Kelly, 2009). Thus most of the studies available in literature are system-centric with an insignificant few being user-centric. There is therefore the need for more user-centric studies that use real life users unlike the laboratory based idea of the system-centric approach that assumes real life users as abstraction (Mandl, 2008). With this need met, more user-centric evaluation studies will occur and the user's aspect of IR evaluative research that is still at its infancy would mature. The bottleneck of using abstract users would then be significantly abated. As a result, the use of naturalistic, quantitative and qualitative studies that will take advantage of real life searchers (Kelly, 2009) would have been encouraged in the evaluation of IR systems.

A number of WebSEs (IR system) such as Google, Lycos, Hotbot, Yahoo, Excite, AltaVista, and lots more exist. How they differ from one another in performance; how to evaluate and measure their effectiveness; where to get existing measures to use to evaluate them; and what their limitations are; are all questions still inviting research? Most, if not all of these questions have been answered using the system-centric approach (Kumar, Suri, and

Chauhan, 2005). But a major challenge with this approach is that the measures used are not usable in the user-centric paradigm. However, both paradigms are recommended in IR literature (Saracevic, 1995; Akhigbe, 2012; Lewandowski and Hochstotter, 2008). This means that existing measures to use to evaluate the IR system from the user-centric aspect are scarce. In this paper, we attempt to underscore the need and importance for introducing the FA technique in user-centric studies in IS. Of particular note is the use of the WebSEs as a case in this paper to underscore the advantages of using the FA technique in IS's assessment. As a result, a measurement model is presented. The process of producing the model is meant to practically show the suitability of FA as a methodology to be trusted in user-related research in IS. This is because its data analysis potentials in user-system interactive modeling is yet to be fully exploited in IS.

6. METHODOLOGY OF RESEARCH

Both online and hardcopy questionnaire was used in a survey to collect the needed data for this research. 250 respondents were randomly sampled. The scale was developed in accordance with the guidelines suggested by Churchill (1979) and Anderson and Gerbing (1988) and it is consistent with the research of Islam (2009), Swaid and Wigand (2009), Sumak *et al.* (2011) and Akhigbe *et al.* (2012). Having, conceptualized the constructs by defining their domains; their dimensions were operationalized following the suggestions of (Kelly, 2009). Additionally, following the approach of Williams *et al.* (2010), the algorithmic like framework was used on the data collected for the research reported in this paper so as to demonstrate the usefulness of the FA technique. This section, therefore presents a description of the development of the measurement instrument, the sampling process and data analysis.

6.1 Development of Measurement Instrument

A total of 17 DVs were presented for data elicitation, using the survey method. The questions were structured in such a way that it was easy to capture discrete data. The DVs were operationalized from within IS domain. The Profile of the respondents used in the study was demographically characterized (see Table 1). A continuum of 5-point Likert scale of: (1) strongly agree; (2) agree; (3) neutral; (4) disagree and (5) strongly disagree, was employed in the rating of users' opinion of any three WebSEs they have used. In order to manage measurement error in the development of the questionnaire a pre-test of the instrument was carried out using a pilot study. As in Sumak *et al.* (2011), the purpose was to improve the item of measurement and confirm that instrument will measure what it is meant for. The Cronbach Alpha (CA) technique was used to test the instrument for internal consistency, and the level of reliability base on the test range from 0.70.

Demographic Characteristics	Demographic Description	Frequency	Percentage
Sex	Male	195	78.0
	Female	55	22.0
Age Range (in years)	16 -25	43	17.34
	26-35	67	26.76
	36-45	120	48.0
	46-55	12	4.70
	55 and above	8	3.2
Status	Student	55	22.0
	Worker	105	41.7
	Lecturer	55	22.0
	Researcher	35	14.2
Internet/Web Experience	Daily	163	72.5
	Weekly	55	21.4
	Monthly	32	6.1
	Never	0	0.0

6.2 Sampling Process

WebSEs have a global spread. In order to capture this both online and hardcopy of our survey instrument was employed for data collection. Unfortunately, the response was not encouraging, since only 250 out of the over 500 requests that was sent out responded. Part of the weakness of the sampling process is the inability to track the responses in order to separate the local and international responses. The approach employed created this tracking difficult, which we hope to check in future studies to be able to report the exact spread. But conservatively, the ratio of International to local responses could be estimated at say 25% to 75%. However, the sample frame used is limited to the demographic characteristics or status in Table 1.

6.3 Statistical Analysis

The EFA technique was used to generate a set of Factor Loadings (FLs) using the PCA, which statistics revealed a priori factor structure (measurement model) that required further testing for reliability and validity. The CFA was used to carry out the reliability and validity testing. Composite Reliability (CR) and Average Variance Extracted (AVE) were used at the level of the constructs (factors) to show the validity of the model; while the Individual Item Reliability (IIR) and FLs were used at the level of items to show the reliability of the model. The cut of points of ≥ 0.6, ≥ 0.5, ≥ 0.4 and ≥ 0.5 were used. The structural part of the model was not necessary since (i) the focus of the analysis was to presents measures that are suitable and replicable for subsequent use, and (ii) the analysis was meant to demonstrate the usefulness of FA in user-centric evaluation in IS. The CFA also served the means to further purify the model. And to find out if the model's goodness-of-fit indices are good enough, the SEM was employed to accomplish this (see Figure 2 for result). The other results of CFA are available in Tables 2 and 3.

Table 2. Results of the Tests for Item's Reliability

IC	FLs	IIR	IC	FLs	IIR
q2	0.777	0.57	q9	0.846	0.70
q3	0.480	0.46	q10	0.840	0.64
q4	0.459	0.68	q11	0.682	0.64
q5	0.742	0.55	q12	0.658	0.59
q6	0.656	0.66	q13	0.595	0.49
q7	0.752	0.71	q15	0.502	0.46
q8	0.793	0.66	q16	0.558	0.43
			q17	0.667	0.45

IC (item code);
FLs (Factor loadings using ≥ 0.5);
IIR (Individual Item Reliability using ≥ 0.4)

Table 3. Measure's Validity

MC	CR	AVE
IA	0.71	0.65
SA	0.71	0.55
SQ	0.72	0.76
U	0.80	0.63

U (Usability); **SQ** (Service Quality);
AVE (Average Variance Extracted using ≥ 0.5);
IA (Information Availability);
CR (Composite reliability using ≥ 0.6);
SA (System's Affordances);
MC (Measures Code)

7. DATA ANALYSIS

The data analysis and results, which is a sine qua non in this research, are given in this section. To do this, this section has been separated into three subsections that are presented as follows.

7.1 Demographic Characteristics

In Table 1, a detailed report of the demographic characteristics of the respondents is presented. From the Table 1; the distinctive respondents are between 36 - 45 years old, most of which are male. The table also reveals that workers used IR systems more, even more than researchers. It is also obvious from the table that respondents had concrete internet experiences (see Table 1). Both measures' reliability and validity, and the suggested Measurement Model (MM) are presented in the next two sections.

7.2 Measures' Reliability and Validity

The statistics of Cronbach's Alpha was used to assess the internal consistency of the constructs. This provided the opportunity for estimating the extent to which multiple indicators for a latent variable belong together. All the estimated CA's values showed all the measurement items were reliable, with all items scoring ≥ 0.7 and above. This further confirmed that the scales from which most of the items were extracted and used were well developed and leave up to de facto standard. The mathematical model employed to produce the CAs are the same with the one in Schmitt (1996) and used in Sumak *et al.* (2011) and Akhigbe *et al.* (2011). For estimating the CR, AVE, IIR and FLs the equations are the same with that of Wu *et al.* (2008) and Sumak *et al.* (2011). In addition all the test results satisfied both internal and external validity of the measurement instrument and scales (see Tables 2 and 3).

7.3 The Measurement Model

The overall fit model that resulted in the final MM (see Figure 2) was estimated to ensure a good data fit. This is consequent upon first subjecting the a priori factor (model) structure from EFA to the CFA statistical rigor, and the secondly the SEM exactitude. As proposed by Rainer and Miller (1996) and used in Wu *et al.* (2008), Swaid and Wigand (2009), and Sumak *et al.* (2011), a variety of fit indices were assessed to ensure this exactitude and identify the MM's goodness-of-fit. The statistics generated for this purpose are: x^2/df (Chi Square/Degree of Freedom); GFI (Goodness of Fit Index); NFI (Normed Fit Index); NNFI (Non-Normed Fit Index); CFI (Comparative Fit Index); RMSR (Root Mean Square Residual); and RMSEA (Root Mean Square Error of Approximation). A summary of the estimated fit indices of the MM are presented beside the MM, using the standard recommended criteria (value) in bracket (see Figure 2). The model – MM is the validated scale, which data is most consistent and is a second-order factor model. This strengthens the fact that the MM retains a multidimensional structure.

Furthermore, the results that brought about the model suggest in entirety that the MM scales (see Figure 2) are reliable. The four subscales - U (Usability); SQ (Service Quality); IA (Information Availability); and SA (System's Affordances) are also reasonably reliable as subcomponents of the overall MM scale. This is consistent with that of Sumak *et al.* (2011), Stephenson *et al.* (2006), and Swaid and Wigand (2009) and as a result of the CA coefficients of .70 and above and the composite 17- item scale (see appendix) and its subscales.

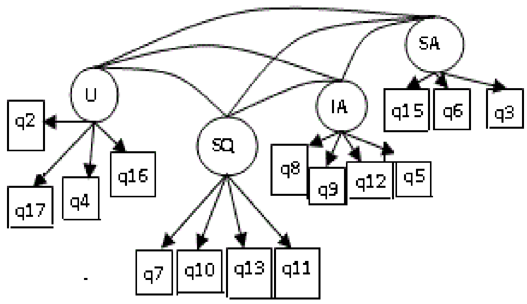

Figure 2. The Measurement Model from CFA

GFI ($\geq$ 0.9) = 0.10
NFI ($\geq$ 0.9) = 0.099
CFI ($\geq$ 0.9) = 0.085
$\mathbf{x^2}$**/df (**$\leq$ 3.00) = 2.55
NNFI ($\geq$ 0.9) = 0.097
RMSR ($\leq$ 0.05) = 0.034
RMSEA ($\leq$ 0.08) = 0.069

The Measurement Model's Goodness-of-fit indices

8. CONCLUSION

This study employed the scale development procedure to establish a 4-factor and 15-item Evaluative Model (EM). This resulted from the need to demonstrate the capability of the FA for data reduction, and also underscore its use for user-centric evaluative research in IS, using the WeSE. The result of the model's testing showed that it provided a high degree of confidence in terms of reliability and validity of the scales. Additionally, the result of the goodness-of-fit of the EM corroborates this since it is within the recommended standard value. The 4-dimensions of the model are: Usability, service quality, information availability, and system's affordances.

The factors (measures) theorize that users' satisfaction with IR system will depend on its ability to provide information as at when needed, but within adequate service delivery. In the use of IR systems, it is necessary for users to be in control of the system in terms of usage. However, items q1 and q14 were deleted during factor loading and extraction. These two items connote system quality. Our insinuation is that technically superior system (system quality) would only be considered successful if it meets users' needs. So, a system may retrieve information very fast, and supported by up-to-date hardware and software; but if its usability is poor and the other 3-dimensions (factors) of the EM is lacking then its acceptability base on usage amidst users will be very low. This study, therefore compliments existing research in which statistics such as ANOVA, Chi-square and T-test are used by demonstrating the potentials of FA over them for user-centric research. This is because unlike others - ANOVA, Chi-square and T-test, FA can handle multivariate data analysis.

The results of this study have implications that would be relevant to different stakeholders in IS and IR domain. A good understanding of the 4-factor that forms the EM would help (i) e-commerce owners and (ii) other related organizations to benefit by possessing the know-how to make more customers, and also deliver quality service to stakeholders. The 15-items of the EM, which cut across 4-factors, would serve useful diagnostic purposes. And researchers in IS could also use the validated scale to evaluate IR systems from the perspective of the user. Both the information provided about the FA technique and the 4-factor EM could serve as a starting point for further research on user-centric evaluative research in IR.

This paper is not without some limitations. The expertise demonstrated with respect to the use of FA still needs a lot of maturing. Secondly, external validity limitations need to be put into consideration in the interpretation of results. Though, the sample used is a fair, it is limited in size. Next, the study is also limited to only WeSEs, thus the generalizations of results are limited to the characteristics and features of WeSEs, hence the need to view the EM with caution. For future work, it will be necessary to examine new variables for suitability in IR system evaluation, but within the context of ISs. Since, ISs are within societal context, we argue that the use of FA is evidently a candidate technique, hence the need to further examine algorithmic issues and implementation. Thus, FA would be well contextualized for IS evaluative research.

ACKNOWLEDGEMENT

We wish to express our appreciation to all, especially those whose papers were reviewed to provide the premise for this study; and to Obafemi Awolowo University, and TETFund for their immense support.

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APPENDIX

Appendix I:
***This appendix contains the 17- item composite (multiple) scale and its subscales* (see Appendix II)**

q1 - The system retrieves information very fast
q2 - The system is easy to use
q3 - The system is clear and understandable to interact with
q4 - Learning to use the system is easy
q5 - It is very easy to express my tasks need to the system
q6 - The user interface of the system is easy to navigate and responds to my tasks needs promptly

q7 - The system is dependable
q8 - I rarely see system failure
q9 - The system's snippet makes it easy to find documents that are relevant to my information need
q10 - The system support even inexperience users with no knowledge to do their job well
q11 - I get the information I need in time
q12 - The system provides up-to-date information
q13 - The system provides prompt service to users
q14 - The system is supported by up-to-date hardware and software
q15 - The system gives clue to help describe information need during query formulation
q16 - It is easy for me to become skillful at using the system
q17 - I find it easy to use the system to do what I want it to do

Appendix II:

The subscales of the 17- item composite (multiple) scale

- (Likert scale) of 1 = strongly agree, 2 = agree, 3 = neutral, 4 = disagree, 5 = strongly disagree.
  Note: The demographic aspect of the questions (items) is as presented in Table I